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# Genetic Algorithm Characterization for the Quality Assessment of Forest Fire Spread Prediction

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## Abstract

When an emergency occurs, hazard evolution simulators are a very helpful tool for the teams in charge of making decisions. These simulators need certain input data, which defines the characteristics of the environment where the emergency is taking place. This kind of data usually constitutes a big set of parameters, which have been previously recorded from observations, usually coming from remote sensors, pictures, etc. However, this data is frequently subject to a high degree of uncertainty, as well as the results produced by the corresponding simulators. Hence, it is also necessary to pay attention to the simulations' quality and reliability. In this work we expose the way we deal with such uncertainty. Our research group has previously developed a two- stage prediction methodology that introduces an adjustment stage in order to deal with the uncertainty on the simulator input parameters. This method significantly improves predictions' quality, however, in order to be useful, a good characterization of the adjustment techniques has to be carried out so that we are able to choose the best configuration of them, given certain restrictions regarding resources availability and time deadlines. In this work, we focus on forest fires spread prediction as a real study case, for which Genetic Algorithms (GA) have been demonstrated to be a suitable adjustment strategy. We describe the methodology used to characterize the GA and we also validate it when assessing in advance the quality of the fire spread prediction.

**Keywords:** Forest Fire Simulation, Data Uncertainty, Emergency Management, Genetic Algorithm

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## 1. Introduction

As it is well stated, tornados, floods, forest fires, and other natural hazards may dramatically threaten people's lives, because of the different kind of drawbacks they can generate, such as disturbing people's daily activities, economic losses, and even breaking the peace of a whole country. For this reason, any effort oriented to minimize the impacts of natural catastrophes is welcome. Due to the difficulty on predicting the occurrence of these phenomena, most of the research efforts are focused on predicting their evolution through time, relying on some physical or mathematical models.

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Nevertheless, environmental hazards represent very difficult systems to simulate. Theoretical and model-related issues aside, many simulators lack precision on their results because of the inherent uncertainty of the data needed to define the state of the system. This uncertainty is due to the difficulty to gather precise values at the right places where the catastrophe is taking place, or because the hazard itself distorts the measurements. So, in many cases the unique alternative consists of working with interpolated, outdated, or even absolutely unknown values. Obviously, this fact results in a lack of accuracy and quality on the provided predictions.

To overcome the just mentioned input uncertainty problem, we have developed a two-stage prediction strategy, which, first of all, carries out a parameter adjustment process by comparing the results provided by the simulator and the real observed disaster evolution. Then, the underlying simulator is executed taking into account the adjusted parameters obtained in the previous phase in order to predict the evolution of the particular hazard for a later time instant. A successful application of this method mainly depends on the effectiveness of the adjustment technique that has been carried out. In this sense, our research group has developed several solutions for input parameters optimization, all of them characterized by an intensive data management: use of statistical approach based on exhaustive exploration of previous fires databases [5], application of evolutionary computation [8], calibration based on domain-specific knowledge [4], and even solutions coming from the merge of some of the above mentioned [7].

It has been demonstrated that the above mentioned adjustment techniques contribute to improve the quality of the predictions. However, a characterization of the adjustment techniques has to be carried out so that we are able to deal with eventual restrictions. These restrictions will be set up at an earlier time instant before starting the calibration and prediction stages, and they may be related to time deadlines, computational resources availability, or both. Therefore, such a characterization must deliver the appropriate parameter settings for executing the underlying adjustment strategy when a certain quality degree prediction is, *a priori*, requested.

This work describes the characterization of GA as adjustment process within the two-stage prediction framework. By means of GA characterization, we state the capability to set up, before starting the whole prediction method, the populations size and the number of GA's iterations that must be executed to satisfy the requested prediction quality.

This paper is organized as follows. In the next section, an overview of how the two-stage prediction method works is given. In Section 3, we expose how this framework could be generalized to any natural hazard, and the methodology to assess in advance the quality of predictions is described. In Section 4, the experimental study is reported and, finally, the main conclusions are included in Section 5.

## 2. Two-stage Prediction Method

Nowadays, scientific community rely on High Performance Computing (HPC) environments in order to solve most of the present scientific problems. Nevertheless, applications which solve such problems still need so much computational resources and time, specially dynamic, event-driven systems simulations.

In the field of physical systems modeling, specifically forest fire behavior modeling, there exist several fire propagation simulators [9, 10, 11], based on some physical or mathematical models [1], which main objective is to try to predict the fire evolution. These simulators need certain input data, which define the characteristics of the environment where the fire is taking place in order to evaluate its future propagation. This data usually consists of the current fire front, terrain topography, vegetation type, and meteorological data such as humidity, wind direction and wind speed. Some of this data could be retrieved in advance and with noticeably accuracy as, for example, the topography of the area and the predominant vegetation types. However, there is some data that turns out very difficult to obtain with reliability. For instance, to get an accurate fire perimeter is very complicated because of the difficulties involved in getting, at real time, images or data about this matter. Other kind of data sensitive to imprecisions is that of meteorological data, which is often distorted by the fire itself. However, this circumstance is not only related to forest fires, but it also happens in any system with a dynamic state evolution (e.g. floods [18], thunderstorms [19, 20], etc.). These restrictions concerning uncertainty in the input parameters, added to the fact that these inputs are set up only at the very beginning of the simulation process, become an important drawback because as the simulation time goes on, variables previously initialized could change dramatically, misleading simulation results. In order to overcome these restrictions, we need a system capable of dynamically obtaining real time input data in those cases that is possible and, otherwise, properly estimating the values of the input parameters needed by the underlying simulator.

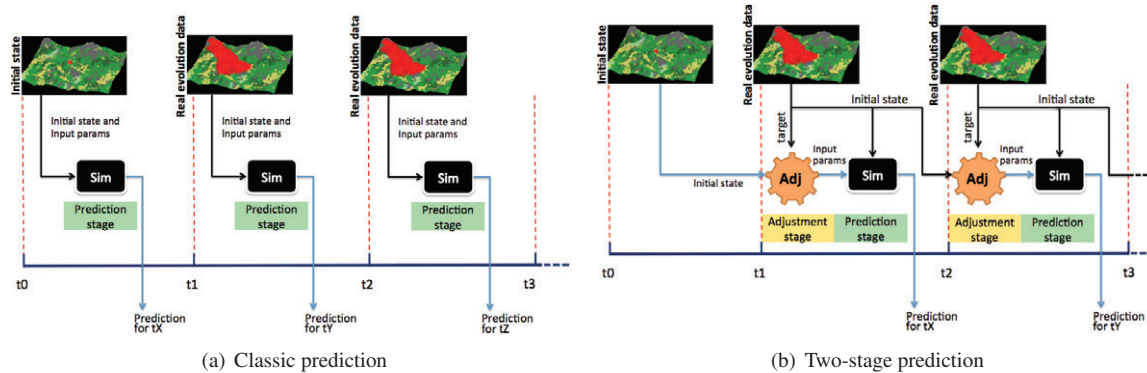


Figure 1: Prediction Methods

The classic way of predicting forest fire behavior, which is summarized in Figure 1(a), takes the initial state of the fire front as input, as well as the input parameters given for a certain time instant. The simulator then returns the fire spread prediction for a later time instant.

Comparing the simulation result with the real fire propagation (later on the experimental section, we describe in more detail how this comparison is conducted), the forecasted fire front tends to differ to a greater or lesser extent from the real fire line. One reason for this behavior is that the classic calculation of the simulated fire is based on one single set of input parameters afflicted with the before explained insufficiencies. To overcome this drawback, a simulator independent data-driven prediction scheme was proposed to optimize dynamic model input parameters [3]. Introducing a previous adjustment step as shown in Figure 1(b), the set of input parameters is optimized before every prediction step. The solution proposed comes from reversing the problem: how to find a parameter configuration such that, given this configuration as input, the fire simulator would produce predictions that match the actual fire behavior. Having detected the simulator input that better describes current environmental conditions, the same set of parameters, could also be used to describe best the immediate future, assuming that meteorological conditions remain constant during the next prediction interval. Then, the prediction becomes the result of a series of automatically adjusted input configurations. It is worth highlighting that, since this two stages spread prediction scheme for forest fire described in Figure 1(b) constitutes a simulator-independent prediction method, the same technique could be extrapolated to any kind of natural disasters by only exchanging the underlying simulator.

This prediction scheme has been demonstrated to deliver better predictions than the classical approach. This is due to the fact that this scheme relies on High Performance Computing platforms by means of executing a huge number of problem simulations on the adjustment stage. Therefore, in order to be operative during a real hazard occurrence, it is necessary to be able to provide in advance reliable prediction results. For this purpose, as we have just mentioned, we need access to a huge number of computing elements. This leads to the necessity of deploying a way to set up in advance:

- The prediction scheme settings, in particular, the calibration policy's specific parameters, for a required prediction's quality. This is specially relevant when the ongoing hazard may threaten urban areas and even human lives.
- The computational resources needed to deliver a required prediction's quality, given a certain time constraints.

This paper focuses on the first point and, in particular, we present the characterization of the Genetic Algorithm (GA) as a calibration scheme. In the next section, we describe in detail how this characterization has been performed.

### 3. Calibration Stage: Genetic Algorithm

Although the subsequent study has been performed for the case of forest fire spread prediction, as we have previously mentioned, it could be extrapolated to any other hazard by simply exchanging the underlying simulator. How-

ever, we need to work under certain assumptions in order to bound the problem and to be able to deliver reliable solutions. Such assumptions are the following:

- We rely on the two-stage prediction strategy under stable environmental conditions.
- We focus on those emergencies where the corresponding simulators present high input-data sensitivity.
- We assume scenarios where the computational resources are dedicated. Currently, we are working on adapting tools that allow urgent execution of tasks in distributed-computing environments, e.g. SPRUCE [14].

It is obvious that in the two-stage prediction strategy, the adjustment process plays the main role. Previous studies demonstrated that the quality of this simulation is directly correlated to the quality obtained at the end of the adjustment process [5]. Thus, it is absolutely necessary to have a good characterization of this process in order to be able to evaluate the adjustment quality we can reach under certain conditions.

For the particular case of forest fire spread prediction, Genetic Algorithm (GA) has been proved to be a good adjustment strategy. As it is well known, GA works in an iterative way. It starts with an initial population of individuals which will be evolved through several iterations in order to guide them to better search space areas. Operators such as *elitism*, *selection*, *crossover* and *mutation* are applied to every population to obtain a new one better than the previous one. Every individual from a population is ranked according to a predefined fitness function. The fitness function in the case of forest fires spread prediction is the difference between real and simulated fire spread (the error formula we use will be detailed in Section 4). The iterative nature of GA leads to an eventually near-optimal solution in the adjustment stage after a certain number of GA iterations. For this reason, it is mandatory to analyze the GA convergence for the particular case of forest fire spread prediction, as well as to be able to extract a general characterization of its behaviour. The analysis of GA convergence is reported in the next section.

#### 4. Genetic Algorithm Convergence Study

In this section, we present the experimental studies carried out to fulfill the need of being able to select, in advance, the best settings for the adjustment method, Genetic Algorithm (GA) in this case, given a certain prediction quality constraint. Many benefits have been previously reported from the use of Genetic Algorithms as a calibration technique [8]. However, by its own nature, this method constitutes a great challenge for the matter we deal with in this work. On the one hand, this technique allows to obtain different degrees of quality on the solutions obtained, which allows us to be able to adapt to eventual restrictions (deadlines, available resources, etc.). On the other hand, this flexibility turns it harder to characterize in order to choose a correct configuration of the method for each case.

Parameters such as number of generations, individuals per population, elitism factor, mutation probability, and so on, affect the quality of the winner individual, i.e. the final solution we will deliver at the end of the adjustment process.

For the characterization of GA, we have carried out massive executions to obtain a proper statistical analysis. Subsequently, we expose the details of the conducted experimental study.

##### 4.1. Test bed description

All the experiments reported in this section have been performed using FARSITE [9] as fire spread simulator. This experiment uses the GIS data from the benchmark provided by FARSITE (the *Ashley project*). Based on this benchmark, we set a reference fire with a duration five hours. All the simulations carried out in this study take these first five hours of spread as the adjustment time interval, and every initial simulation setting (i.e. every individual in the GA) is configured according to the probability distributions and their associated parameters shown in Table 1 for each type of input parameter (i.e. each gene of each individual). As regards wind speed and wind direction, these probabilities correspond to the ones used in [17]. Vegetation models correspond to the 13 standard Northern Forest Fire Laboratory (NFFL) fuel models [2].

The final fire front of the reference fire is taken at the end of each simulation in order to calculate the difference between it and the simulated one. We call this difference *adjustment error*, and it is calculated by means of the following formula:

$$E = \frac{(UnionCells - InitCells) - (IntersectionCells - InitCells)}{RealCells - InitCells} \quad (1)$$

This equation calculates the differences in the number of cells burned, both missing or in excess, between the simulated and the real fire. *UnionCells* is the union of the number of cells burned in the real fire and the cells burned in the simulation, *IntersectionCells* is the intersection between the number of cells burned in the real fire and in the simulation, *RealCells* are the cells burned in the real fire and *InitCells* are the cells burned at the starting time.

Regarding the GA configuration, in this particular set of experiments we fixed both the elitism factor (10%), and the number of generations (5), and we performed a study based on the results obtained from the evolution of 50 populations composed of 100 individuals for each case, and setting the mutation probability to 10%.

As regards the computational platform, all the experiments carried out in this work were done on a cluster of 8 x Dell PowerEdge M600 nodes, each of which counting on 2xQuad-Core Intel Xeon E5430, 2.66GHz, 2x6MB L2 cache memory (2x2) and 16 GB RAM Fully Buffered DIMMs 667MHz, running Linux version 2.6.16.

Input	Distribution	$\mu, \sigma$	Min, Max
Vegetation model	Uniform	—	1,13
Wind Speed	Normal	12.83,6.25	—
Wind Direction	Normal	56.6,13.04	—
Dead fuel moisture	Uniform	—	0,1
Live fuel moisture	Uniform	—	0,4

Table 1: Input parameters distributions description.

#### 4.2. Statistical Study

From the obtained results, a statistical study carrying out the Kolmogorov-Smirnov, Anderson-Darling, and Chi-squared tests allowed us to determine that the probability distribution which better fits the obtained data is the *Logistic distribution*, which resembles the normal distribution, but presents higher kurtosis. Its probability density function is the following one:

$$pdf(x; \mu, s) = \frac{e^{-(x-\mu)/s}}{s(1 + e^{-(x-\mu)/s})^2} \quad (2)$$

In this equation,  $x$  is the random variable (which corresponds to the obtained adjustment error),  $\mu$  is the *location* factor, which is analogous to the mean value in a normal distribution, and  $s$  is the *scale* factor, which is proportional to the standard deviation, both of them needed to define such probability distribution. Although the probability distribution of the data is the same in the whole evolution process, these factors vary depending on the iteration of the GA we are evaluating. So, Figure 2 depicts the different probability density functions for each generation. Figure 3 shows the obtained values for both the location and scale factors at each generation of the evolution process.

By means of these probability density functions we are able to guarantee, with different degrees of certainty, the maximum adjustment error we will obtain given a certain configuration of the GA (in this particular case, populations of 100 individuals, and both elitism and mutation factor set to 10%). Besides, since the number of evolved generations has a direct impact on both the available resources and time needed to perform the adjustment process, it is worth highlighting the fact that we are able to give this guarantee taking into account the number of generations we are able to execute. Symbols G1-G5 correspond to the number of generation within the evolution process.

Table 2 shows the different maximum adjustment errors (considering the adjustment time interval [0 hours - 5 hours]) for which we have different *degrees of guarantee*, depending on the number of generations the GA iterates.

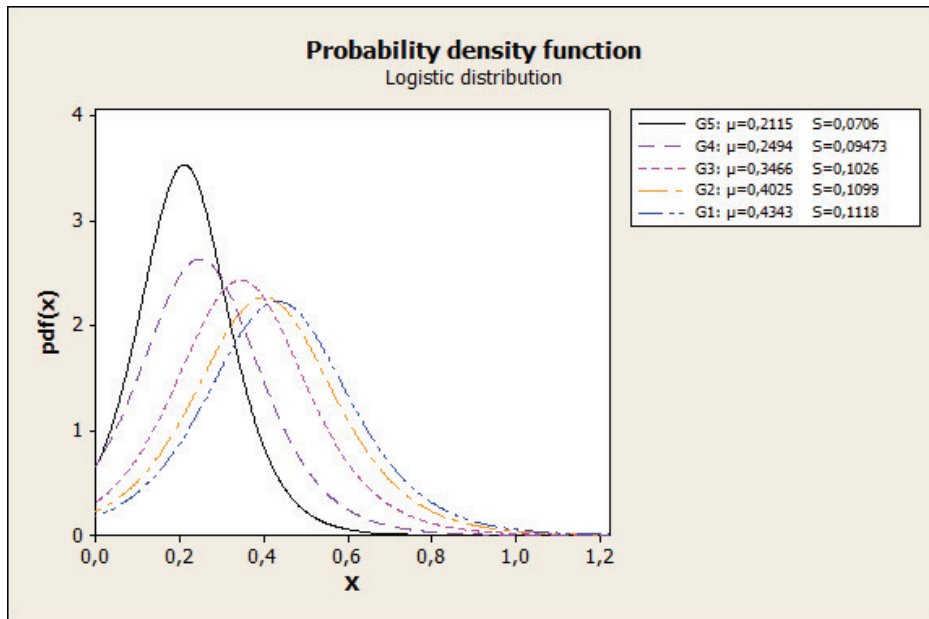


Figure 2: Probability density functions for the obtained errors at each generation of the evolution process

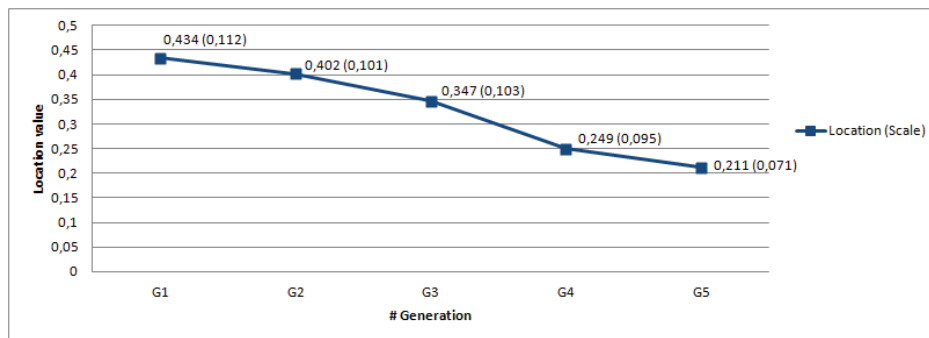


Figure 3: Location and scale values obtained after the evolution of 50 populations for the calibration interval ( 0hours - 5hours )

Here, *guarantee degree* stands for the probability to obtain an adjustment error lesser or equal than the specified value, on the basis of the above presented probability density function (Equation 2).

Figure 4 also depicts this information, from a guarantee degree of 95% down to 75%. As it is easily understandable, the lesser the error requested is, the lesser the degree of guarantee, for the same number of iterations of the GA.

Considering a real situation, where the quality of the prediction is a parameter fixed by the decision control centre in charge of making the appropriate decisions about how to fight against the ongoing fire, this information turns out to be very important, since we are able to give a certain guarantee of quality in the final prediction, taking into account how many evolution steps (i.e. how many generations) we can perform. This, as previously stated, will be determined by the available computational resources and time to deliver a prediction. In the subsequent subsection we expose a validation experiment which confirms this study.

#### 4.3. Experimental Validation

Once the above exposed statistical analysis has been carried out, we present a validation test by means of which we can prove that this characterization methodology is suitable for the problem we tackle.



Guarantee degree	G1	G2	G3	G4	G5
95%	0.763	0.726	0.649	0.528	0.419
90%	0.680	0.644	0.572	0.458	0.367
85%	0.628	0.593	0.525	0.414	0.334
80%	0.589	0.555	0.489	0.381	0.309
75%	0.557	0.523	0.459	0.353	0.289
70%	0.529	0.496	0.434	0.330	0.271
65%	0.504	0.471	0.410	0.308	0.255
60%	0.480	0.447	0.388	0.288	0.240
55%	0.457	0.425	0.367	0.268	0.226
50%	0.434	0.403	0.347	0.249	0.211

Table 2: Maximum adjustment errors and degrees of guarantee, depending on the number of GA generations

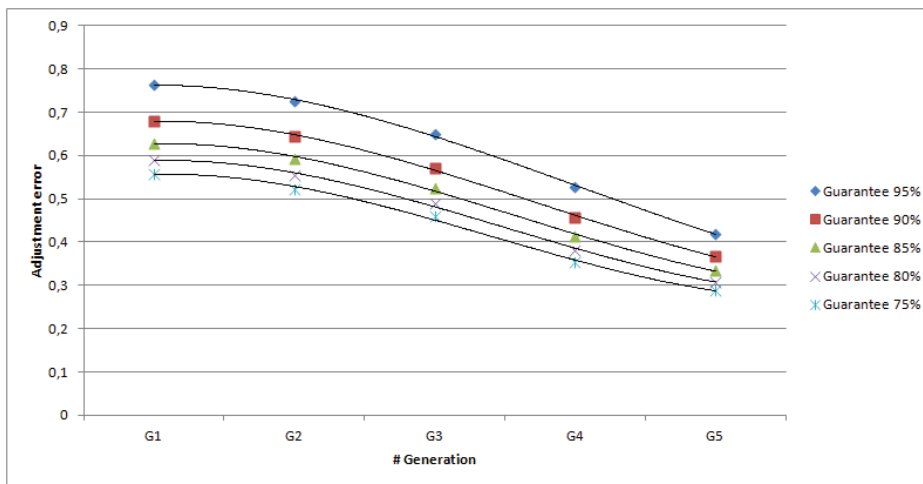


Figure 4: Maximum adjustment errors and degrees of guarantee

For this purpose, we carried out the adjustment process, considering the adjustment time interval [0 hours - 5 hours], for five new random populations (p0 - p4) in the case of a new different fire. Specifically, as in the test bed described in Section 4.1, we used FARSITE as the fire propagation simulator, as well as the same GIS data, but we changed completely the conditions of the reference fire, so its spread varied significantly.

As regards the GA configuration, the five new populations were composed of 100 individuals, both elitism and mutation factor were set to 10%, and again we performed five-generation evolution process.

Table 3 shows the obtained errors for each population. In order to contrast this data with the guaranteed errors exposed in Table 2, let us consider three cases of different guarantee degrees in our estimations before the adjustment process was carried out:

- Estimation with 95% degree of guarantee: in this case, all of our estimations were right, with the exception of the errors obtained at generation 1 of populations p1, p3 and p4, which present very high adjustment errors. This fact was expected, and it is understandable, since because of the random features of genetic algorithms, only one step of evolution is not enough at all to determine any kind of significant approach to a suitable solution, so is not enough to give an estimation with any degree of guarantee.
- Estimation with 85% degree of guarantee: again, we failed in the estimations of populations p1, p3 and p4 at generation 1. However, for the rest of generations, we only failed in one estimation at generation 4 (population p2), and one in generation 5 (population p0), which is acceptable taking into account this guarantee degree.

Population	G1	G2	G3	G4	G5
p0	0.601	0.376	0.376	0.376	0.376
p1	0.993	0.450	0.450	0.125	0.096
p2	0.433	0.433	0.433	0.433	0.309
p3	0.823	0.332	0.105	0.105	0.105
p4	0.894	0.343	0.343	0.323	0.323

Table 3: Adjustment errors for populations p0-p4 for the calibration interval ( 0hours - 5hours )

- Estimation with 75% degree of guarantee: in this case, we failed in populations p0, p1, p3 and p4 at the end of generation 1. At the end of generation 4, we failed in our estimations in the cases of populations p0 and p2. At the end of generation 5, we failed in three cases: populations p0, p2 and p4. In this specific case of guarantee degree we have obtained worse results, since we expected a 25% probability of fail, that is, one or two fails for a set of five populations. However, the difference between the guaranteed error and the ones obtained for those populations is so small, what leads us to consider that in a greater set of populations, the guarantee degree in our estimations would fit the results obtained.

These three different cases validate our proposal, so we are able to establish, in advance, adjustment error boundaries in our prediction framework. This turns out to be very important for the final predictions, since the adjustment error and final prediction error in our two-stage prediction method are highly correlated [5]. Besides, we introduce a degree of certainty in our future predictions, which is very valuable at the time of making decisions.

Moreover, this methodology allows to assess different possibilities regarding the number of generations to perform in the GA process, which is also very useful, depending on the amount of computational resources and time available to perform a prediction.

## 5. Conclusions

Natural hazard management is undoubtedly a relevant application area in which the Computational Science can play a very important role. In this kind of phenomena, it is usual to have to deal with high degrees of uncertainty on the input parameters, which may lead us to important losses as regards predictions' quality.

In this work, we detail our two-stage prediction method by the use of which it has been demonstrated, in previous works, that we are able to relieve the drawbacks produced by such uncertainty, and therefore, enhancing the quality of prediction. However, for this strategy to be useful, it is necessary to follow a proper methodology so that we are able to estimate, in advance, how it will perform.

This work constitutes a part of a project which consists of determining in advance, how a certain combination of natural hazard simulator, computational resources, adjustment strategy, and frequency of data acquisition will perform, in terms of execution time and prediction quality.

Since we are dealing in the area of natural hazards management, it is absolutely necessary to be able to assess in advance the quality of the predictions that will be delivered by means of our prediction framework. This is very important for the control centers to make the appropriate decisions in each case.

In this work, we focus on the specific case of forest fires, as a one of the most worrisome natural disasters, and the experimental studies have been done using the FARSITE simulator.

We have exposed our methodology to characterize a well-known Artificial Intelligence technique as adjustment strategy, Genetic Algorithms, which has demonstrated to be a powerful technique to perform the adjustment process in our two-stage prediction method.

For this purpose, we have carried out a statistical study based on a huge set of simulations. Then, we have identified the probability distribution which corresponds to the obtained results, so that we can rely on its probability density function in order to establish certain degrees of guarantee in our adjustment errors estimations.

Furthermore, this study allows us to make decisions about which specific setting of the GA is the most appropriate given time and resource availability restrictions, and it allows us to tackle this problem in different ways, by designing different policies to optimize the use of the available computational resources. This constitutes part of our ongoing and



future work, and includes, for example, the ability to group fastest simulations in subsets of computational resources, allocating the slowest ones in other dedicated subsets, according to the specific needs of each case.

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